KNN Project Exercise - Solutions

Due to the simplicity of KNN for Classification, let's focus on using a PipeLine and a GridSearchCV tool, since these skills can be generalized for any model.

The Sonar Data

Detecting a Rock or a Mine

Sonar (sound navigation ranging) is a technique that uses sound propagation (usually underwater, as in submarine navigation) to navigate, communicate with or detect objects on or under the surface of the water, such as other vessels.

The data set contains the response metrics for 60 separate sonar frequencies sent out against a known mine field (and known rocks). These frequencies are then labeled with the known object they were beaming the sound at (either a rock or a mine).

Our main goal is to create a machine learning model capable of detecting the difference between a rock or a mine based on the response of the 60 separate sonar frequencies.

Data Source: https://archive.ics.uci.edu/ml/datasets/Connectionist+Bench+(Sonar,+Mines+vs.+Rocks) (https://archive.ics.uci.edu/ml/datasets/Connectionist+Bench+(Sonar,+Mines+vs.+Rocks))

Complete the Tasks in bold

TASK: Run the cells below to load the data.

```
In [95]: import numpy as np
         import pandas as pd
         import seaborn as sns
         import matplotlib.pyplot as plt
```

```
In [6]: df = pd.read_csv('sonar.all-data.csv')
```

```
In [7]: df.head()
```

```
Out[7]:
     Freq1   Freq2   Freq3   Freq4   Freq5   Freq6   Freq7   Freq8   Freq9  Freq10  ...  Freq52  Freq53  Freq54  Freq55  Freq56  Freq57  Freq58  Fr
  0  0.0200  0.0371  0.0428  0.0207  0.0954  0.0986  0.1539  0.1601  0.3109  0.2111  ...  0.0027  0.0065  0.0159  0.0072  0.0167  0.0180  0.0084  0.
  1  0.0453  0.0523  0.0843  0.0689  0.1183  0.2583  0.2156  0.3481  0.3337  0.2872  ...  0.0084  0.0089  0.0048  0.0094  0.0191  0.0140  0.0049  0.
  2  0.0262  0.0582  0.1099  0.1083  0.0974  0.2280  0.2431  0.3771  0.5598  0.6194  ...  0.0232  0.0166  0.0095  0.0180  0.0244  0.0316  0.0164  0.
  3  0.0100  0.0171  0.0623  0.0205  0.0205  0.0368  0.1098  0.1276  0.0598  0.1264  ...  0.0121  0.0036  0.0150  0.0085  0.0073  0.0050  0.0044  0.
  4  0.0762  0.0666  0.0481  0.0394  0.0590  0.0649  0.1209  0.2467  0.3564  0.4459  ...  0.0031  0.0054  0.0105  0.0110  0.0015  0.0072  0.0048  0.

5 rows × 61 columns
```

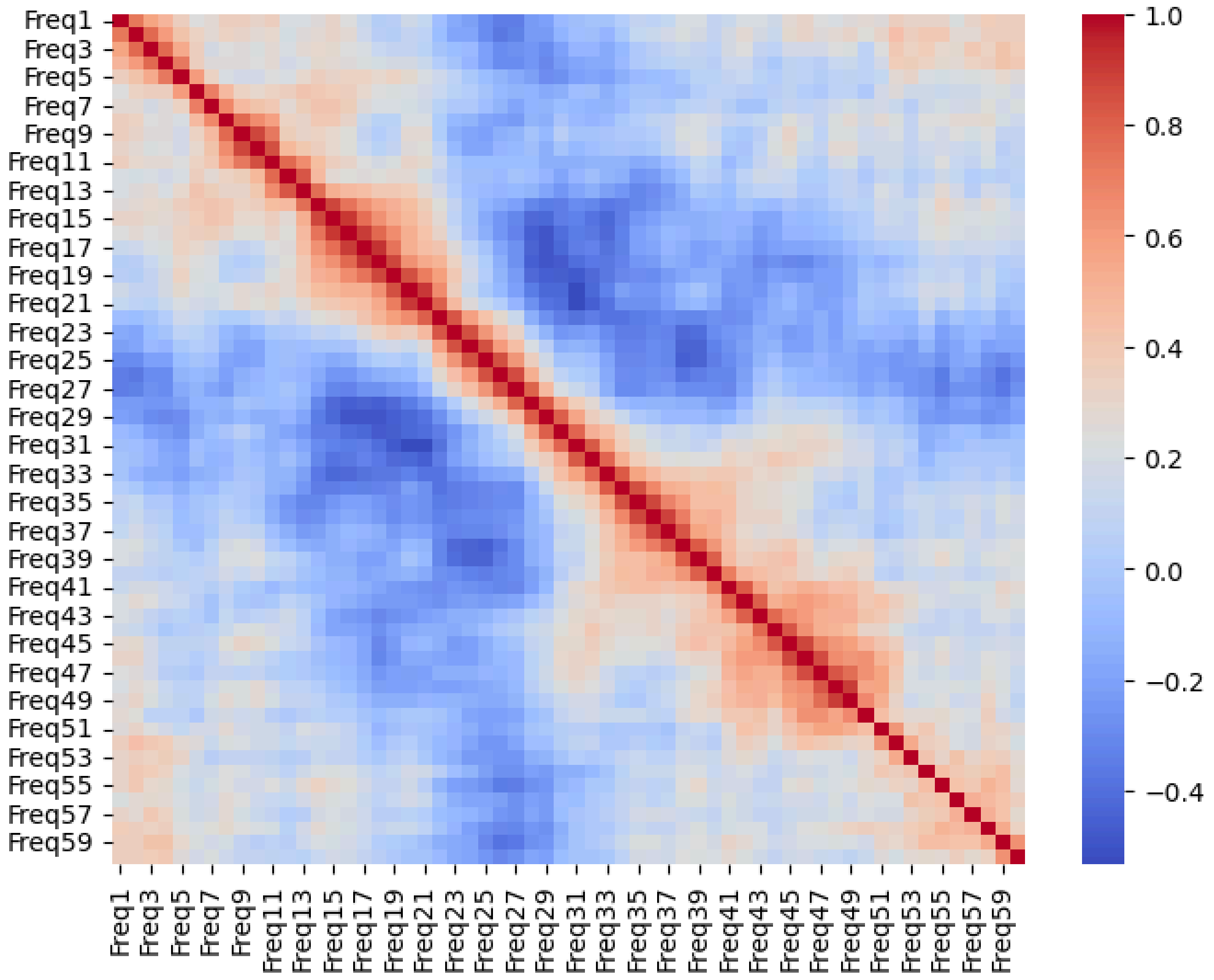
Data Exploration

TASK: Create a heatmap of the correlation between the difference frequency responses.

```
In [ ]: # CODE HERE
```

In [8]:
```
plt.figure(figsize=(8,6))
sns.heatmap(df.corr(),cmap='coolwarm')
```

Out[8]:
```
<AxesSubplot:>
```



TASK: What are the top 5 correlated frequencies with the target\label?

Note: You many need to map the label to 0s and 1s.

*Additional Note: We're looking for **absolute** correlation values.*

In [99]:
```
#CODE HERE
```

In [9]:
```
df['Target'] = df['Label'].map({'R':0,'M':1})
```

In [10]:
```
np.abs(df.corr()['Target']).sort_values().tail(6)
```

Out[10]:
```
Freq45    0.339406
Freq10    0.341142
Freq49    0.351312
Freq12    0.392245
Freq11    0.432855
Target    1.000000
Name: Target, dtype: float64
```

Train | Test Split

Our approach here will be one of using Cross Validation on 90% of the dataset, and then judging our results on a final test set of 10% to evaluate our model.

TASK: Split the data into features and labels, and then split into a training set and test set, with 90% for Cross-Validation training, and 10% for a final test set.

In [102]:
```
# CODE HERE
```

In [11]:
```
from sklearn.model_selection import train_test_split
```

In [12]:
```
X = df.drop(['Target','Label'],axis=1)
y = df['Label']
```

In [13]:
```
X_cv, X_test, y_cv, y_test = train_test_split(X, y, test_size=0.1, random_state=42)
```

TASK: Create a PipeLine that contains both a StandardScaler and a KNN model

In [14]:
```
from sklearn.preprocessing import StandardScaler
from sklearn.neighbors import KNeighborsClassifier
```

In [15]:
```
scaler = StandardScaler()
```

In [16]:
```
knn = KNeighborsClassifier()
```

In [17]:
```
operations = [('scaler',scaler),('knn',knn)]
```

In [18]:
```
from sklearn.pipeline import Pipeline
```

In [19]:
```
pipe = Pipeline(operations)
```

TASK: Perform a grid-search with the pipeline to test various values of k and report back the best performing parameters.

In [20]:
```
from sklearn.model_selection import GridSearchCV
```

In [21]:
```
k_values = list(range(1,30))
```

In [22]:
```
param_grid = {'knn__n_neighbors': k_values}
```

In [23]:
```
full_cv_classifier = GridSearchCV(pipe,param_grid,cv=5,scoring='accuracy')
```

In [25]:
```
import warnings
warnings.filterwarnings('ignore')

full_cv_classifier.fit(X_cv,y_cv)
```

Out[25]:
```
GridSearchCV(cv=5,
             estimator=Pipeline(steps=[('scaler', StandardScaler()),
                                       ('knn', KNeighborsClassifier())]),
             param_grid={'knn__n_neighbors': [1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11,
                                              12, 13, 14, 15, 16, 17, 18, 19,
                                              20, 21, 22, 23, 24, 25, 26, 27,
                                              28, 29]},
             scoring='accuracy')
```

In [26]:
```
full_cv_classifier.best_estimator_.get_params()
```

Out[26]:
```
{'memory': None,
 'steps': [('scaler', StandardScaler()),
  ('knn', KNeighborsClassifier(n_neighbors=1))],
 'verbose': False,
 'scaler': StandardScaler(),
 'knn': KNeighborsClassifier(n_neighbors=1),
 'scaler__copy': True,
 'scaler__with_mean': True,
 'scaler__with_std': True,
 'knn__algorithm': 'auto',
 'knn__leaf_size': 30,
 'knn__metric': 'minkowski',
 'knn__metric_params': None,
 'knn__n_jobs': None,
 'knn__n_neighbors': 1,
 'knn__p': 2,
 'knn__weights': 'uniform'}
```

(HARD) TASK: Using the .cv_results_ dictionary, see if you can create a plot of the mean test scores per K value.

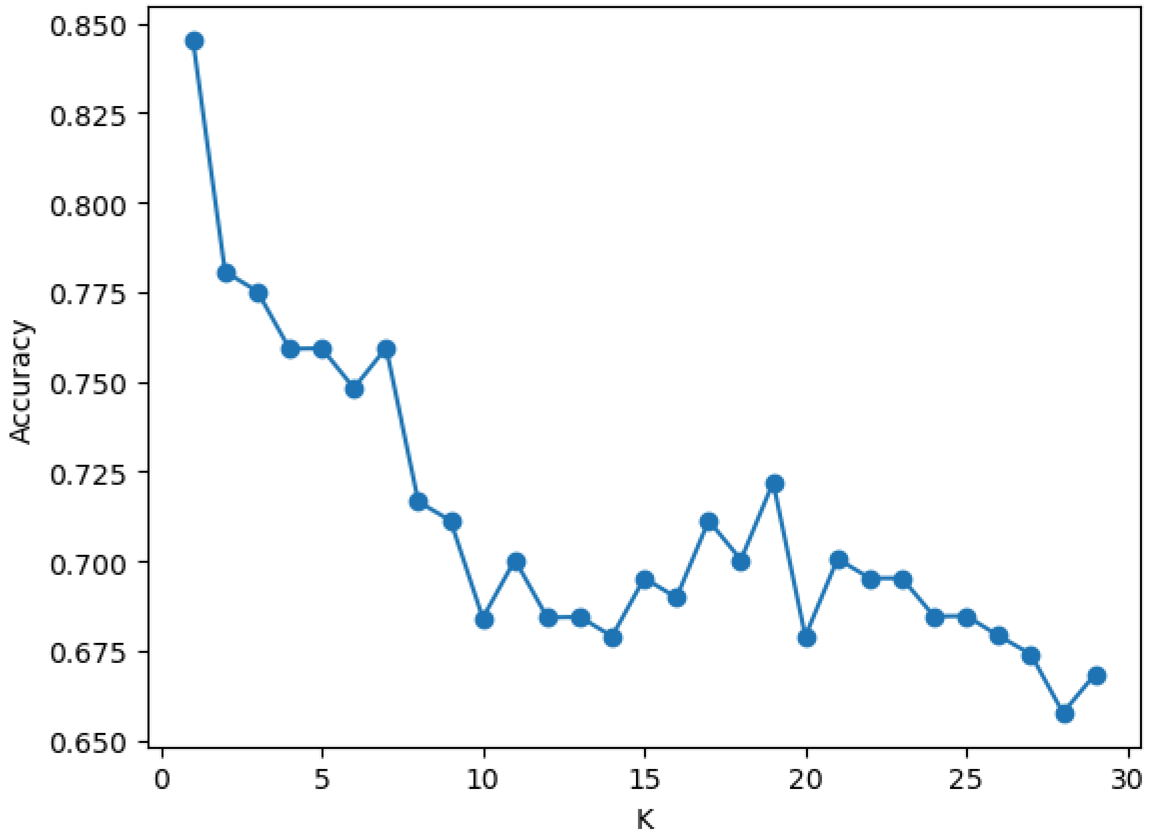
In [113]:
```
#CODE HERE
```

In [27]:
```
full_cv_classifier.cv_results_['mean_test_score']
```

Out[27]:
```
array([0.84537696, 0.78065434, 0.77524893, 0.75917496, 0.75931721,
       0.74822191, 0.75945946, 0.71664296, 0.7113798 , 0.68421053,
       0.70042674, 0.68435277, 0.68449502, 0.67908962, 0.69530583,
       0.68990043, 0.7113798 , 0.70042674, 0.72204836, 0.67908962,
       0.70071124, 0.69530583, 0.69530583, 0.68463727, 0.68477952,
       0.67923186, 0.67411095, 0.65775249, 0.6685633 ])
```

```
In [28]: scores = full_cv_classifier.cv_results_['mean_test_score']
         plt.plot(k_values,scores,'o-')
         plt.xlabel("K")
         plt.ylabel("Accuracy")
```

```
Out[28]: Text(0, 0.5, 'Accuracy')
```



Final Model Evaluation

TASK: Using the grid classifier object from the previous step, get a final performance classification report and confusion matrix.

```
In [117]: #Code Here
```

```
In [29]: pred = full_cv_classifier.predict(X_test)
```

```
In [30]: from sklearn.metrics import classification_report,confusion_matrix,accuracy_score
```

```
In [31]: confusion_matrix(y_test,pred)
```

```
Out[31]: array([[12,  1],
                [ 1,  7]], dtype=int64)
```

```
In [32]: print(classification_report(y_test,pred))
```

```
              precision    recall  f1-score   support

           M       0.92      0.92      0.92        13
           R       0.88      0.88      0.88         8

    accuracy                           0.90        21
   macro avg       0.90      0.90      0.90        21
weighted avg       0.90      0.90      0.90        21
```

Great Job!